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Abstract

In the automobile industry, as in many tradable goods markets, firms earn their highest market share within their domestic market. This home market advantage persists despite substantial integration of international markets during the past several decades. The goal of this paper is to quantify the supply- and demand-driven sources of the home market advantage and to understand their implications for international trade and investment. Building on the random coefficients demand model developed by Berry, Levinsohn, and Pakes (1995), we estimate demand and supply in the automobile industry for nine countries across three continents, allowing for unobserved taste and cost variation at the car model and market levels. While trade and foreign production costs as well as taste heterogeneity matter for market outcomes, we find that preference for domestic brands is the single most important driver of home market advantage - even after controlling for brand histories and dealer networks.

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1 Introduction

In tradable goods industries, it is typical for firms to earn their highest market shares in their domestic market. This home market advantage persists despite substantial integration of international markets during the past several decades. There is no shortage of explanations (e.g., trade costs, investment frictions, home preference, taste heterogeneity for characteristics) for this empirical regularity, but different explanations have substantially different policy implications. The goal of this paper is to quantify the sources of the home market advantage, and to understand the implications of these frictions for international trade and investment. In particular, what is the role of tariff and non-tariff barriers, transportation costs, and foreign production costs in explaining global market outcomes? How important are consumer preferences, either for particular characteristics or simply for national brands? The automobile industry provides an interesting case for analyzing these questions. The industry accounts for over 10 percent of world trade in manufactured goods (WTO, 2013) and bears the features of many oligopolistic industries producing differentiated and tradable goods, while domestic producers command a dominant share in their home markets.

Apart from its importance in world trade and manufacturing employment, the availability of data also makes the auto industry suitable for our analysis. We have compiled a rich and unique dataset of global demand and supply. The demand data informs us about prices and quantities (as opposed to sales revenue only) by model as well as several characteristics such as horsepower, size, weight and fuel efficiency in nine countries across three continents. On the supply side, we have worldwide data on the assembly plant locations of each model. We propose a structural model which exploits two features of the data to separate preference-based incentives to purchase local products from supply side frictions such as trade and investment costs. First, the availability of price data allows us to measure the willingness to pay for models. Second, the prevalence of foreign direct investment (FDI) provides variation between national brand identity and assembly location, helping to disentangle their demand and supply effects. Moreover, we are able to separately identify country-level preferences for characteristics (such as fuel efficiency) from home preference—an innate preference for purchasing local products.[1]

[1]In a world with trade costs and increasing returns to scale, local producers may obtain larger national market shares for reasons distinct from home preference if they happen to supply the goods that are in high relative demand there (Krugman, 1980).

Separating the underlying drivers of home market advantage is important to understand how globalization affects market outcomes and welfare. In particular, consider the response to trade liberalization. In the absence of preference-based drivers, one would expect the home market advantage to vanish if all trade barriers were removed. As pointed out by Auer (2014), if cross-country heterogeneity in taste for characteristics is a strong feature of the economy, trade will respond sluggishly after a trade liberalization. Strong home preference would further weaken the response.

Traditionally, models of international trade have relied on relatively restrictive demand systems (e.g. constant elasticity of substitution in Krugman 1980, Eaton and Kortum 2002, Melitz 2003, and Anderson and van Wincoop 2003) to analyze market outcomes.[2] While these approaches represent tractable means of analysis, they may be limited in their ability to capture rich substitution patterns that are a feature of horizontally differentiated oligopolistic industries such as cars. Quantitative applications have also been limited by the availability of only revenue data without credible price and quantity information. As a result, they may lead to biased estimates of trade costs and an underappreciation of preference differences across national markets. We incorporate a random coefficients approach to estimating demand, allowing for both within- and across-market heterogeneity in consumer preferences. This more flexible approach enables us to consistently estimate demand- and supply-driven mechanisms behind market segmentation.[3] Our approach further enables the estimation of costs of foreign production from detailed industry level data and extends the analysis of recent quantitative trade models with multinational production (Ramondo and Rodriguez-Clare 2013, Arkolakis, Ramondo, Rodriguez-Clare, and Yeaple 2013, and Tintelnot 2014), which were also limited by the availability of only revenue data on multinationals' foreign affiliate sales for the aggregate manufacturing sector.

We build on the random coefficients demand model developed by Berry, Levinsohn, and Pakes (1995), who study the U.S. automobile market. This framework uses a flexible structural approach

[2] With the notable exception of non-homothetic preferences (Fieler (2011), Fajgelbaum, Grossman, and Helpman (2011), Fajgelbaum and Khandelwal (2014)) which are used to rationalize a certain pattern in the trade data, namely the prevalence of north-north trade. However, in that literature consumer preferences are identical across countries and it is income levels that vary.

[3] In previous work (Coşar, Grieco, and Tintelnot 2015), we estimated supply-side border frictions in wind turbine trade using detailed geographic data on firm sales.

to recover firm markups in a differentiated products market with multi-product firms.[4] Due to the knowledge of assembly locations, we can include trade cost shifters as instruments for price in the demand estimation. After recovering demand elasticities, we back out costs via optimal pricing strategies. Using variation in assembly and headquarter locations, we estimate trade and foreign production costs, as well as the cost of supplying of each characteristic. We allow for the fact that the source location is endogenously chosen from the set of all available plants. Overall, we estimate both demand and supply in a consistent framework that allows for unobserved demand and cost heterogeneity at the model and market levels.

We use our estimates to unpack the contributions of tariffs, trade/FDI costs, home preference, and taste heterogeneity to home market advantage. To quantify home market advantage, we calculate the difference in market share when a model is sold at home versus abroad, controlling for model and market fixed effects. We find that, on average, a model's home market share is more than triple its share abroad—albeit from a small base, given that there are more than 200 models competing in most markets. Using our structural estimates, we then evaluate the contributions of potential drivers of the home market advantage by computing counterfactual prices and shares after removing various potential drivers of market segmentation and re-computing the home market advantage statistic. We find that home market advantage is most sensitive to the removal of home preference for domestic brands, declining by about 60 percent. In contrast, when we remove all supply-related frictions, the home market advantage declines by only 13 percent. This finding points to home preference as a key missing element of the trade and multinational production literatures. Home preference may arise due to nationalistic feelings among consumers or through the ability of home brands to provide unobserved characteristics (body styling, interior features such as cup holders) that better fit their home market. Importantly, our results are obtained controlling for the impact of a brand's entry date into a market and dealer density. Since, for historical reasons, these factors are correlated with home status, treating them as unobserved would lead to even larger estimates of home preference.

A number of papers have looked at the car industry to study questions in international trade. Among them, Feenstra (1988), Goldberg (1995), and Berry, Levinsohn, and Pakes (1999) analyze

[4] In an alternative approach, De Loecker and Warzynski (2012) use plant level production data to recover markups in a trade setting.

the effects of Japanese voluntary export restraints on the American auto market. Goldberg and Verboven (2001b) study price dispersion in the European car market and also find evidence for consumers favoring national brands. Goldberg and Verboven (2004) use panel data from the car industry to demonstrate a strong positive effect of the Euro on price convergence. Brambilla (2005) investigates firms' responses to trade policy in South America. McCalman and Spearot (2013) study firms' offshoring strategies using data on North American light truck production locations. More recently in contemporaneous work, Head and Mayer (2015) estimate a model of international trade and foreign production using sourcing data from the automotive industry, finding that foreign sales are impeded significantly by trade, foreign production, and multinational sales frictions. Similar to our paper, the latter captures a general disadvantage in selling outside the home market. Our contribution is to disentangle the demand and supply related components of this disadvantage.[5]

Our findings are related to Atkin (2013) who demonstrates that neglecting taste heterogeneity for food leads to biased estimates of gains from trade. They also complement an extensive literature in marketing illustrating the importance of brand preferences (Bronnenberg, Dhar, and Dube 2009, Bronnenberg, Dube, and Gentzkow 2012). Relative to these papers, we contribute by jointly analyzing cost and preference differences across markets and quantifying their impact in an international context.

The next section describes the data and presents the stylized facts motivating our analysis. Section 3 formulates a model of international competition in the automobile market. We estimate the model in Section 4 and evaluate the drivers of home market advantage in Section 5. We conclude in Section 6.

2 Data and Descriptive Evidence

Our data set covers the market for passenger cars in 6 EU countries (Belgium, Germany, France, Italy, Spain, Great Britain), Brazil, Canada and the US for the period 2007-2011.[6] For each available market-year, we observe model-level sales (i.e. number of new cars sold), prices (MSRP)

[5] While their dataset reports model level flows between all assembly locations and many more destination markets, our dataset has more detailed information about the product—most notably, prices and characteristics—in fewer yet important markets. Having information on prices and quantities separately is key in identifying demand from supply-related factors.

[6] Brazilian market data is missing for 2007 and Canadian data is available for 2008-2009 only. Total sales cover more than 90% of total new passenger car sales in the European markets and 80% of sales in the American markets.

Table 1: Market concentration

	Sales	Firms	Top 5	Brands	Top 5	Models	Top 5
BEL	496,165	20	0.68	39	0.44	314	0.13
BRA	2,555,502	17	0.82	23	0.81	98	0.36
CAN	1,137,453	16	0.65	34	0.50	207	0.22
DEU	3,011,972	20	0.71	38	0.54	323	0.18
ESP	1,082,867	21	0.72	39	0.44	290	0.16
FRA	2,045,998	20	0.81	38	0.65	271	0.25
GBR	2,026,497	22	0.63	39	0.47	311	0.21
ITA	2,016,114	22	0.70	41	0.51	283	0.26
USA	10,390,308	19	0.68	40	0.53	291	0.14

Notes: Average number of passenger cars sold annually in each country over the data period. Market shares by top manufacturing group (firms), brands and models are revenue-based.

and product characteristics (such as length, width, weight, and fuel efficiency). The characteristics of a model are the sales-weighted average trim-level characteristics and vary across markets and years. We also constructed a data set of assembly locations informing us about the countries in which the models in our demand data were assembled in any given year. We complement this data set with market-specific variables such as gas prices, import tariffs on cars, sales taxes, the level and dispersion of household income as well as brand-market specific variables such as a brand's entry date into a market and number of car dealers. Appendix A describes the construction of the data set.

Some manufacturing groups own multiple brands. In what follows, we distinguish firms (manufacturing groups such as GM and VW), brands (such as Vauxhall and Opel owned by GM, Audi and Seat owned by VW) and models (such as Vauxhall Corsa and Opel Corsa). In cases where a firm owns foreign brands, we distinguish the headquarter country from a brand's nationality. For example, GM is a US firm, but Vauxhall and Opel are British and German brands, respectively. In other words, a brand's nationality is defined as the country from which it historically originates. Across all years and markets, the data set encompasses 28 firms, 60 brands and 597 models. Firms are headquartered in 12 different countries, and brands are associated with 15 different countries.

Next, we document a number of facts that influence our modeling of the industry. We conclude the section with a hedonic regression which is informative for our use of instruments later in the paper.

The oligopolistic nature of the car industry is well known. While measures of concentration

Table 2: Market shares by brand nationality

	Market share of brands from						
	DEU	ESP	FRA	GBR	ITA	USA	Other
BEL	0.34	0.02	0.26	0.02	0.04	0.09	0.23
BRA	0.23	-	0.11	0.00	0.23	0.31	0.12
CAN	0.07	-	-	0.01	-	0.34	0.58
DEU	**0.55**	0.02	0.09	0.01	0.03	0.08	0.21
ESP	0.26	**0.09**	0.26	0.01	0.03	0.11	0.22
FRA	0.19	0.02	**0.52**	0.01	0.04	0.07	0.16
GBR	0.23	0.02	0.13	**0.18**	0.02	0.16	0.25
ITA	0.24	0.01	0.15	0.02	**0.30**	0.12	0.17
USA	0.08	-	-	0.01	0.00	**0.40**	0.52

Notes: Each row presents the revenue-based market share of brands originating from countries listed in the columns, adding up to one subject to rounding error. - means that brands from the origin country are not sold in the market, and 0.00 implies a market share of less than one percent. Other includes Japan, Korea, China, India, Sweden, Malaysia, Czech Republic, Romania and Russia. The bottom panel excludes these "other" countries and presents market shares within the brand-owning producers in our dataset.

vary across markets (Table 1), the top 5 firms account for an average of 55% of total revenues across all market-years. Similarly, the market share of the top 5 brands is 35%.

Table 2 presents market shares by brand nationality. The diagonal in bold highlights the dominance of home brands (Belgium, Brazil and Canada do not have a national brand in our data set). Spanish and British brands have marginal sales outside of their markets. Similarly, Italian brands have low sales in other European markets but a stronger presence in Brazil due to FDI. The most striking difference is between Germany and France: in both markets, home brands account for more than half of the sales, whereas German brands' market share in France is only 19%, which is relatively higher than the French market share of 9% in Germany.

Brands' differential market shares across countries are driven by an extensive margin of model offerings as well as an intensive margin of sales per model. In order to decompose these two margins, we follow Bernard, Jensen, Redding, and Schott (2009) and start with the identity

$$s_{bmt} \;=\; \bar{s}_{bmt} \cdot N_{bmt},$$

where s_{bmt} is the share of brand b in total market m sales in year t, and N_{bmt} is the number of

Table 3: Market share decomposition

Variable	I	II	III	IV
	$\ln(\bar{s}_{bmt})$	$\ln(N_{bmt})$	$\ln(\bar{s}_{bmt})$	$\ln(N_{bmt})$
$\ln(s_{bmt})$	0.619	0.381	0.578	0.422
	(0.007)	(0.006)	(0.007)	(0.007)
Observations	1471	1471	1471	1471
R^2	0.810	0.617	0.781	0.654
Share	Units	Units	Revenue	Revenue
Margin	Intensive	Extensive	Intensive	Extensive

Notes: Standard errors in parentheses. This table shows the share of variation in s_{bm} coming from the intensive margin (average model market share of the brand) and the extensive margin (number of models offered by the brand). Accordingly, columns 1 and 2 as well as columns 3 and 4 add up to one. All regressions are estimated with year fixed effects.

models offered. We then separately project $ln(N_{bmt})$ and $ln(\bar{s}_{bmt})$ on $ln(s_{bmt})$. Table 3 reports the results. The intensive margin accounts for 58 to 62 percent of the overall variation, depending on whether the market share is in revenues or units sold. Variation in the popularity of brands across countries is not simply due to the number of products offered.

To gauge the extent of the home market advantage, we project market shares on a dummy variable that takes the value one if a model is at home and zero otherwise. Table 4 presents the results. First two columns are the brand-market-year (bmt) level, while the last column is at the model-market-year (jmt) level. Given the importance of the extensive margin documented above, column II also controls for the (log) number of models that the brand offers. Fixed effects control for brands' and models' global popularity and market-year specific conditions. We find a large and significant home market effect: being a home brand increases market share at the model-level by 238 percent.[7] We label this effect "home market advantage."

Table 5 presents average prices and characteristics (weighted by sales) of cars sold in each market. We observe MSRP price in each country. In countries with a retail sales tax, we augment this price with the retail sales tax so it approximates the effective price to the consumer. The average car in the North American market is larger in horsepower and size (columns 2 and 3) and less fuel efficient (column 4) than the typical car sold in Europe and Brazil. Differences in gas

[7] Following Kennedy (1981) and van Garderen and Shah (2002), we calculate home market advantage using $100 \cdot (\exp(\hat{c} - \frac{1}{2}V(\hat{c})) - 1)$, where $\hat{c}$ is the coefficient on the dummy for being a home brand and $V(\hat{c})$ is the estimate of its variance.

Table 4: Home market advantage

Variable	I	II	III
	$\ln(s_{bmt})$	$\ln(s_{bmt})$	$\ln(s_{jmt})$
Home brand	1.675	1.066	1.219
	(0.082)	(0.061)	(0.032)
$\ln(N_{bmt})$		1.533	
		(0.042)	
Observations	1471	1471	8834
R^2	0.794	0.895	0.720
Market-year FE	Yes	Yes	Yes
Brand FE	Yes	Yes	
Model FE			Yes

Notes: Standard errors in parentheses. All regressions are estimated with market-year (mt) fixed effects. First two columns are at the brand-market-year (bmt) level and use brand fixed effects. The last column is at the model-market-year (jmt) and uses model fixed effects.

prices, however, affect the average cost of a mile (last column) that consumers face in each market. While some of this variation is due to the extensive margin, characteristics also differ within models. Controlling for model fixed effects, we see less powerful engines and much higher fuel economy in European countries and Brazil compared to the North American market (see Table B.1 in Appendix B). These systematic differences highlight the importance of controlling for product characteristics when estimating consumer demand.

On the production side, there are 50 countries that assemble cars. 43% of the models (255 out of 598) are assembled in more than one country, accounting for 64% of total revenue. The market share of models assembled in 5 or more countries is 30% (see figure B.1 in the appendix). While we do not know the exact sources of supply, we can analyze each market in terms of potential sources of supply. Column 1 of Table 6 presents the average number of countries in which models consumed in a particular market are assembled. For instance, there are 3.8 countries in which models sold in Brazil are assembled (weighted by models' market shares in Brazil), while models sold in Canada are assembled in 5 countries. The nearest of these plants is on average 1,885 km away from Brazilian consumers while models sold in Canada and the US are assembled in more

Table 5: Prices and characteristics

	Price	HP/Wt	Size	MPG	Gas price	MPD
BEL	32,578	58.4	7.6	34.4	7.3	4.7
BRA	23,801	62.3	6.8	30.1	5.6	5.4
CAN	30,507	91.8	8.3	22.3	2.9	7.6
DEU	35,940	66.8	7.6	29.3	7.3	4
ESP	31,790	60.8	7.6	32.6	5.4	6.1
FRA	29,712	57.2	7.3	35.5	7	5.1
GBR	31,390	65.5	7.5	30.4	7	4.3
ITA	27,654	57.6	7	33.4	7.2	4.7
USA	28,867	97.9	8.7	21	3.1	6.7

Notes: All variables are averages over models weighted by market share over the data period. Prices are in USD, converted from local currency using mean yearly exchange rates and averaged over the data period. HP/Wt denotes horsepower per weight (kg) times 1,000. Size is meter length times meter width. MPG is miles per gallon. Gas prices are per gallon in USD. MPD is miles per dollar (MPG/price).

distant locations (column 2).[8] Geography, units costs and trade policy are important determinants of these potential supply locations. Brazil is the most protected country in our data set, with an MFN import tariff on cars equal to 35%, and the US is the most open, with an MFN import tariff of 2.5%.[9] (column 4). The resulting tariff-jumping FDI leads to a higher market share for the models that are assembled domestically (column 3).

To gain some initial insight into how model characteristics and supply location correlate with prices, Table 7 presents the results of a reduced form regression of price including model and market-year fixed effects. While this regression is unable to distinguish demand and supply effects from each other, it does give an indication of how equilibrium price moves as model features change. As expected, horsepower per weight, size and fuel efficiency, are all associated with higher prices. The coefficient on distance to nearest assembly is also positive and significant. Under the assumption that consumers do not care about distance to assembly after controlling for other factors, this result implies that assembly distance has some power as an instrument for demand. Most interestingly, being assembled at home is negatively correlated with price, while being a home brand is positively

[8] These figures include internal distance within a country. We use bilateral and internal distances from the CEPII data (Mayer and Zignago 2011) calculated as population-weighted distances between the biggest cities of two countries. Internal distances range from 66 km in Belgium to 1,853km in the U.S.

[9] The so-called US "chicken tax" of 25% applies on light trucks, which we exclude from our analysis. SUVs are imported as passenger cars.

Table 6: Supply locations

	Supply Locations	Average Distance	Domestic Share (%)	MFN Tariff (%)
BEL	4.4	1095	9	10
BRA	3.8	1885	87	35
CAN	5	3670	26	6.1
DEU	4.7	1077	51	10
ESP	4.5	1627	33	10
FRA	4.2	1026	41	10
GBR	4.5	1440	17	10
ITA	4	1333	20	10
USA	4.2	3625	54	2.5

Notes: Supply locations is the average number of countries in which models sold in a market are assembled, weighted by models' market share. Average distance is the average distance across models to the closest supply location, weighted by models' market share. Domestic share is the market share of models which have an assembly plant in the country. Implied internal distances capture differences in land area across countries. MFN (most favored nation) is the non-discriminatory tariff rate applied to WTO members that are not in a free trade agreement with the country.

associated with price. These two features can be separated due to foreign direct investment: some home brands are produced abroad and imported while some foreign brands are assembled within the market. This finding supports our assumption in the structural model below that brand nationality affects the demand for cars, while cars' assembly location affects their production costs.

Table 7: Price regression

	$\ln(price_{jmt})$
$\ln(hppwt_{jmt})$	0.258
	(0.0107)
$\ln(size_{jmt})$	0.538
	(0.039)
$\ln(mpd_{jmt})$	0.0194
	(0.0096)
$\ln(dist_{jmt})$	0.0192
	(0.0016)
Domestic assembly	-0.0158
	(0.0035)
Home brand	0.0192
	(0.0033)
Observations	8835
R^2	0.985
Market-year FE	Yes
Model FE	Yes

Notes: See table 5 for the description of parameters. Home brand is one if a model belongs to a national brand and zero otherwise. Domestic assembly is one if there is an assembly plant for a model in the country and zero otherwise. Regression controls for market-year and model fixed effects.

3 Model

We model the national market for cars in a given calendar year. We first give a brief overview of the model describing the assumptions on the timing of actions. We then discuss demand and supply in more detail using notation in the subsections below.

Manufacturers are endowed with a set of models (i.e., Toyota Corolla, Toyota Camry, etc.) to sell within the market. Each model is endowed with a set of characteristics (e.g., size, fuel efficiency) and a set of assembly locations where the model can be produced. At the start of the year, all manufacturers observe a set of demand and supply shocks for each model that are uncorrelated with model or assembly location characteristics. This assumption implies that a manufacturer chooses to offer a car in a location before observing the model-market demand or supply shock. This assumption—which is common to many random coefficients demand estimations (e.g., Berry, Levinsohn, and Pakes, 1995)—is reasonable in our context because while it is relatively easy to adjust a car's price in reaction to local market conditions, the decision to release a model in a country generally involves a significant design period prior to entry. Similarly, moving the assembly of a certain model to a plant requires a planning and retooling time. Having observed their own and competitors' demand and supply shocks, manufacturers simultaneously choose prices at the model level according to a Nash-Bertrand equilibrium. We follow the literature on automobile pricing in assuming that prices are set at the model level and consumers face a single price. Consumers then observe these prices and make purchases. Finally, automakers select the assembly location from which to source ordered cars. We allow for heterogeneity in production costs at the car-assembly location level so that a manufacturer may choose to source cars from multiple assembly locations to supply the same model to a market.

3.1 Demand

The utility to consumer i in market m from purchasing model j is,[10]

$$u_{jmi} \;=\; \bar{u}(x_{jm}, p_{jm}, \beta_{mi}, \alpha_{mi}) + \xi_{jm} + \varepsilon_{jmi} \tag{1}$$

where x_{jm} represents the model characteristics—e.g. horsepower per weight, size, fuel efficiency, or brand fixed effects—and p_{jm} represents the price. The terms β_{mi} and α_{mi} represent tastes for characteristics and price sensitivity, respectively. Differences in β_{mi} across individuals and countries may arise due to innate preferences or differences in the prices of complimentary goods such as parking space and gasoline.

Individual tastes are distributed according to a market-specific distribution $(\beta_{mi}, \alpha_{mi}) \sim F_m(\,\cdot\,|\theta^d)$, where θ^d is a vector of parameters. Each model receives a market-year specific demand shock, ξ_{jm}, that is common to all consumers within a market. Finally, each consumer receives an idiosyncratic utility shock for each model, ε_{jmi}, which is distributed according to the Type-I extreme value distribution.

Consumers in each market observe the set of available products and choose the model that maximizes their utility from all available models and a no-purchase option. We normalize the utility of the no-purchase option to $u_{0mi} = \varepsilon_{0mi}$. Let C_m be the set of cars consumers can choose

[10] For readability we omit the time subscript, t, from the model section.

from within market m. Each consumer chooses the option that maximizes her utility,

$$d_{mi} = \underset{j \in C_m \cup 0}{\text{argmax}} \; u_{jmi}.$$

Integrating out the idiosyncratic consumer taste shock, we have the probability that each consumer buys a car given their tastes $(\beta_{mi}, \alpha_{mi})$,

$$Pr(d_{mi} = j|\beta_{mi}, \alpha_{mi}) = \frac{e^{\bar{u}_{jmi}+\xi_{jm}}}{1 + \sum_{k \in C_m} e^{\bar{u}_{kmi}+\xi_{km}}}.$$

Market shares for model j can be calculated by integrating these individual-specific probabilities over the distribution of consumer tastes in the market.

$$s_{jm} = \int Pr(d_{mi} = j|\beta_{mi}, \alpha_{mi}) dF_m(\beta_{mi}, \alpha_{mi}|\theta^d). \tag{2}$$

The demand parameters, θ^d, govern the distribution of tastes. Following Berry, Levinsohn, and Pakes (1995), we will estimate these parameters by inverting the share equation to recover ξ_{jm} and constructing a set of moment conditions using exogeneity restrictions.

3.2 Supply

Manufacturers supply models to consumers by sourcing them from available assembly locations, which were determined prior to demand and cost shocks being revealed to the firms. The cost of sourcing a car i of model type j for market m from location ℓ is,

$$c_{jm\ell i} = c_1(h_{jm}, \kappa) c_2(g_{jm\ell}, \delta) e^{\omega_{jm} - \nu_{jm\ell i}} \tag{3}$$

where $c_1(\cdot)$ represents model- and market-specific costs of selling model j in market m, which are determined by a vector of observable model and market characteristics h_{jm} (such as global production costs of the vehicle and local distribution costs) and a vector of parameters κ. Similarly, $c_2(\cdot)$ represents the effect of costs due to sourcing model j from an assembly plant in location ℓ to be sold in market m. It depends on a vector of known market-assembly-model characteristics $g_{jm\ell}$ (such as distance to the sourcing country from the market and firm's headquarter location and productivity in the assembly location) and a vector of parameters δ. The structural error term ω_{jm} represents a shock to the marginal costs of selling model j in a given market m. Finally, costs at the car level are affected by an idiosyncratic shock, $\nu_{jm\ell i}$. This final cost is revealed to the manufacturer at the time a car is ordered, but after prices for models are set. Producers have full knowledge of ω_{jm} and all other cost shifters besides $\nu_{jm\ell i}$ when setting prices. As we show below, the idiosyncratic error $\nu_{jm\ell i}$ introduces the possibility of "gains from diversification" in assembly locations and rationalizes the possibility that some models are sourced from multiple assembly locations.

Given this model for costs, the manufacturer minimizes costs by sourcing cars from the lowest cost location from its set of available assembly locations, L_j,

$$c_{jmi} = \min_{\ell \in L_j} c_{jm\ell i}.$$

However, the firm must set prices prior to the $\nu_{jm\ell i}$ shock being revealed; therefore it must set prices according to its expected cost of supplying a model by integrating over $\nu_{jm\ell i}$. We assume $\nu_{jm\ell i}$ is distributed Type-I extreme value with scale parameter σ_ν.[11] Given this assumption, the probability of sourcing a car from location ℓ is,

$$\begin{aligned} Pr(i \text{ is sourced from } \ell) &= \frac{\exp\left(\frac{-\log c_2(g_{jm\ell},\delta)}{\sigma_\nu}\right)}{\sum_{k\in L(j)} \exp\left(\frac{-\log c_2(g_{jmk},\delta)}{\sigma_\nu}\right)} \\ &= \frac{c_2(g_{jm\ell},\delta)^{-1/\sigma_\nu}}{\sum_{k\in L(j)} c_2(g_{jmk},\delta)^{-1/\sigma_\nu}}, \end{aligned} \tag{4}$$

where we exploit the fact that minimizing cost is equivalent to maximizing the negative of the logarithm of cost. Therefore, the logarithm of the average marginal cost to sell a car of model j is,[12]

[11] We could relax the assumption that $\nu_{jm\ell i}$ is independent across i at the cost of additional notation. For example, we could divide the year into an large number of discrete time sub-periods and let each consumer who purchases a car within a sub-period receive the same draw of $\nu_{jm\ell i}$. This would be consistent with the shock reflecting unanticipated backlogs or shocks to assembly location productivity during the year.

[12] A constant from integrating the Type-1 extreme value distribution is absorbed in $\log c_1(h_{jm}, \kappa)$.

$$\log c_{jm} = \log c_1(h_{jm}, \kappa) - \sigma_\nu \log\left(\sum_{k\in L(j)} \exp\left(\frac{-\log c_2(g_{jmk}, \delta)}{\sigma_\nu}\right)\right) + \omega_{jm}. \quad (5)$$

Or equivalently, the average marginal cost is,

$$c_{jm} = c_1(h_{jm}, \kappa)\left(\sum_{k\in L(j)} c_2(g_{jmk}, \delta)^{-1/\sigma_\nu}\right)^{-\sigma_\nu} \exp(\omega_{jm}). \quad (6)$$

In these expressions, the second term captures the fact that manufacturers endogenously choose to source cars from the lowest cost locations. The intuition behind this formula is straightforward. Lower cost locations are more likely to be used as sources, which is reflected in the fact that they contribute the most to the sum over locations. Moreover, as more locations are added, this sum increases, further reducing costs. The value of σ_ν captures "gains from variety" in the sense that the value of an additional assembly location is scaled by σ_ν. Furthermore, as $\sigma_\nu \to 0$, firms always source from the single location that has the lowest average cost and (5) becomes,

$$\lim_{\sigma_\nu\to 0} \log c_{jm} = \log c_1(h_{jm}, \kappa) + \min_{k\in L(j)}\left\{\log c_2(g_{jmk}, \delta)\right\} + \omega_{jm}.$$

So as $\sigma_\nu \to 0$, only variation in g_{jmk} at the minimum cost location affects the marginal cost of a model. The supply side parameters to estimate are $\theta^s = (\delta, \kappa, \sigma_\nu)$.

3.3 Pricing Equilibrium

Firms choose prices to maximize profits given demand and the average marginal cost of a model c_{jmt}, which is determined by the cost minimization across available assembly locations. Since a mass of consumers purchase cars, c_{jmt} is exactly known to manufacturers when they set prices, even though they do not know $\nu_{jm\ell i}$ until consumer i purchases a car. For the same reason, firms know from (2) exactly what the shares will be given a vector of prices within the market p_m. Therefore, firm f's profit maximization problem is to choose prices for its portfolio of models within a market J_m^f to maximize profits,[13]

[13] We control for differences in tax regime across markets using country market dummies in the specification of costs. The model could be explicitly extended to account for differing tax regimes (e.g., value added versus retail sales tax) given stronger assumptions how the base for these regimes is determined.

$$\max_{\{p_{jm}\}_{j\in J_m^f}} \quad \sum_{j\in J_m^f} \left[p_{jm} - c_{jm}\right] \cdot N_m \cdot s_{jm}(p_{jm}; p_m^{-j}), \tag{7}$$

where N_m is the exogenous number of potential buyers and p_m^{-j} is the vector of prices for models other than j. A Nash-Bertrand equilibrium strategy profile is a vector p_m such that $s_{jm} = s_{jm}(p_m)$ and all firms are maximizing profits. Therefore, prices satisfy the system of first order conditions for every price, p_{jm},

$$s_{jm}(p_m) + \sum_{k\in J_m(f)} \left[p_{km} - c_{km}\right] \frac{\partial s_{km}(p_m)}{\partial p_{jm}} \; = \; 0. \tag{8}$$

3.4 Identification

The demand parameters are identified via moment condition assumptions on the model-market demand shocks ξ_{jm}. As shown by Berry (1994), there is a one-to-one mapping between the demand shocks and observed market shares given demand parameters and observed prices. So, given a demand parameter θ^d, we can numerically recover the complete vector of demand shocks within a market,

$$\xi_m \; = \; s^{-1}(s_m, p_m; \theta^d).$$

We then identify the model using a vector of instruments z_{jm} such that $E[\xi_{jm} z_{jm}] = 0$. The model precludes price from being used as an instrument since it is endogenously determined. We use three types of instruments. First, model characteristics (e.g., x_{mj})—which are determined before demand shocks are realized—are uncorrelated with demand shocks, though they will clearly be correlated with price. Second, as discussed in Berry, Levinsohn, and Pakes (1995), characteristics of other models are similarly available as instruments, since they affect prices though the markup term in (8).[14] Finally, functions of observed variables that affect costs $(h_{jm}, g_{jm\ell})$ may be used as instruments since they are uncorrelated with the demand shock ξ_{jm} but affect prices through the costs in (8). In our case, these variables are the drivers of trade costs, such as the distance to assembly locations. We have experimented with all three types of instruments, and use all three in

[14]These instruments have been recently been criticized by Armstrong (2014) relating to the viability of markup instruments when there are a large number of firms. These predictions are corroborated by Monte Carlo simulations performed by Conlon (2013).

our preferred specification.

With the demand parameters identified, we are able to recover marginal cost for each model by inverting the firms' first order conditions at observed prices and shares as in Nevo (2001). For clarity, we suppress the market subscripts and focus on a single market. Given demand parameters and observed prices and shares, all the terms in (8) are known with the exception of c_j. Note that firms internalize their cross-price effect on other models that they sell, but not on competitor models. If we define Ω such that,

$$\Omega_{jk} \;=\; -\frac{\partial s_k(p)}{\partial p_j} \cdot \mathbf{1}[j,k \text{ jointly owned}],$$

then we can write (8) in vector notation, $s(p)-\Omega(p-c)=0$, and can easily solve this for the vector of marginal costs,

$$c \;=\; [p-\Omega^{-1}s(p)].$$

Once costs are recovered, we can identify the cost side parameter θ^s from (5) and the assumption that $E[\omega_{jm}|(h_{jm}, g_{jm\ell})] = 0$. While identification of model- and market-specific costs, κ, is straightforward given regularity conditions that will be satisfied by our parameterization, the contribution of trade- and location-specific production costs, parameterized by δ and σ_ν, are more subtle.[15] First, consider identification of σ_ν, the variance of the idiosyncratic car cost shock. Suppose that all assembly locations were identical and geography was symmetric, that is for a given model, $c_2(g_{jm\ell}, \delta) = \bar{c}_2$. In this case, the only reason to source from a particular location would be due to the extreme value error, $\nu_{jm\ell i}$. There would be a cost advantage to operating multiple assembly locations in that you would get a new draw of this idiosyncratic cost shock for each location. Therefore, the extent to which marginal costs decline as we vary the number of production locations identifies σ_ν. In the extreme, suppose $\sigma_\nu = 0$. Then, an additional assembly location will not reduce marginal costs at all. With σ_ν identified, we can identify the parameters on assembly location characteristics from the variation in these characteristics. This variation will affect average costs in two ways. First, it will change the cost associated with that assembly location conditional on it being used, and second, it will change the probability that the plant is used to source cars.

[15] We are assuming a location normalization in $c_2(g_{jmk}, \delta)$, as is common in discrete choice models, without loss of generality. A scale normalization on σ_ν is not necessary as we explain below.

Again, consider the extreme case when $\sigma_\nu = 0$. Then, *only* variation in the lowest-cost assembly location's characteristics affect average costs. Therefore, variation in an assembly characteristic across locations first identifies which is the lowest cost and then identifies the parameter for that characteristic based on the size of the change in costs. If σ_ν is positive, then variation in characteristics of all assembly locations affect costs, but its impact is weighted by the quantity of cars each location provides. In summary, each element of δ is identified as long as it affects $c_2(g_{jm\ell}, \delta)$ for some model j where trade flows are positive between market m and assembly location ℓ. This is the case even though we do not directly observe trade flows because we can use variation in model costs, c_{jm}, and $g_{jm\ell}$ to infer the effect of δ.

4 Estimation

The model is estimated in two stages. We first estimate the demand side. We then use firms' profit maximization conditions and the estimated demand parameters to recover the marginal cost of supplying each model to each country. Finally, we use these recovered costs to estimate the supply side.[16] Since we use data from multiple years, we introduce a time subscript, t, below.

4.1 Demand Parameterization and Estimation

We start by parameterizing the utility function to be quasi-linear in price, and quadratic in tastes for characteristics:

$$\begin{aligned} \bar{u}(x_{jmt}, p_{jmt}, \beta_{mi}, \alpha_{mti}) &= \beta_{mi}^{hp} \,\text{hppwt}_{jmt} + \beta_{m}^{hp2} \,\text{hppwt}_{jmt}^2 \\ &+ \beta_{mi}^{sz} \,\text{size}_{jmt} + \beta_{m}^{sz2} \,\text{size}_{jmt}^2 \\ &+ \beta_{mi}^{md} \,\text{mpd}_{jmt} + \beta_{m}^{md2} \,\text{mpd}_{jmt}^2 \\ &- \alpha_{mti}\, p_{jmt} + \iota_t + \psi_{mb(j)}, \end{aligned} \tag{9}$$

where hppwt_{jmt} is the horsepower of the car divided by its weight (a measure of acceleration capability), size_{jmt} is the size of the car (length times width in meters), and mpd_{jmt} is miles per dollar at market price for gas (according to city fuel efficiency rating). This specification allows for

[16] In principle, demand and supply can be estimated jointly, which would improve efficiency at the cost of computational tractability.

consumers' marginal taste for a characteristic to be increasing or decreasing in the amount of the characteristic provided. For example, we would expect the marginal utility of size to decrease as a car gets larger. We further assume that linear tastes are normally distributed around a market-specific mean with common variance across markets,[17]

$$\begin{bmatrix} \beta_{mi}^{hp} \\ \beta_{mi}^{sz} \\ \beta_{mi}^{md} \end{bmatrix} \sim N\left(\begin{bmatrix} \bar{\beta}_{m}^{hp} \\ \bar{\beta}_{m}^{sz} \\ \bar{\beta}_{m}^{md} \end{bmatrix}, \begin{bmatrix} \sigma_{hp}^2 & 0 & 0 \\ 0 & \sigma_{sz}^2 & 0 \\ 0 & 0 & \sigma_{md}^2 \end{bmatrix} \right),$$

while the quadratic parameters are market-specific but are constant across consumers within a market. This specification leads to the intuitive interpretation that a model with size_{jmt} provides a marginal utility for size to the median consumer within market m as given by

$$\text{med}\left(\frac{\partial u_{jmti}}{\partial \text{size}_{jmt}} \right) \; = \; \bar{\beta}_{m}^{sz} \; + \; 2\beta_{m}^{sz2} \, \text{size}_{jmt},$$

while other consumers' marginal utility for size is normally distributed around this level with variance σ_{sz}^2.

Consumers' price-sensitivity, α_{mti}, is distributed log-normally conditional on consumer i's income according to,

$$\log \alpha_{mti} \sim N(\bar{\alpha} + \pi_{\alpha} \log \text{inc}_{mti}, \sigma_{\alpha}^2).$$

Letting price sensitivity vary with income allows for non-homotheticity of preferences. Because we do not observe individual consumers, we simulate their income, inc_{mti}, from a log normal distribution fitted to mean household income and the Gini ratio for each market.

The final two terms in (9) are time and brand-country fixed effects. Time fixed effects capture global shocks to automobile demand. The brand-country fixed effect, $\psi_{mb(j)}$, captures revealed preference for different brands within each country.[18] For each model j, $b(j)$ represents its brand. The same firm may operate multiple brands. That is, the Toyota Corolla is of brand 'Toyota' while

[17] In principle we could allow the variances to vary by market, however because they enter the objective function in a nonlinear way, doing so would greatly increase the computational complexity of estimation. Moreover, since we have only 4-5 years of data from each market it is unclear that these parameters could be precisely estimated at the market level.

[18] As a robustness check, we have also estimated a version of the model with model fixed effects that are constant across countries.

the Lexus RX 450 is of brand 'Lexus' even though they are offered by the same firm (Toyota). Separating brands within firms is important since firms frequently use branding as a method of accentuating vertical differentiation. To the extent that consumers exhibit a preference for their home brands, this preference is absorbed into these brand-country fixed effects.

Under this parameterization of the demand model, $\theta^d = (\bar{\beta^x_m}, \beta^{x2}_m, \sigma_x, \bar{\alpha}, \pi_\alpha, \sigma_\alpha, \iota_t, \psi_{mb})$ represents the parameters to estimate, where $x \in \{hp, sz, md\}$. As discussed above, given θ^d and the observed market shares, there is a one-to-one mapping to the vector of demand shocks $\xi(\theta^d)$. We approximate the market shares using Halton sequences to integrate out the distribution of consumers taste, and solve this mapping numerically to recover the demand shocks implied by the data for a given parameter values. We estimate the model by minimizing the generalized method of moments objective function,

$$\hat{\theta}^d = \underset{\theta^d}{\operatorname{argmin}}\, \xi(\theta^d)' Z \hat{W} Z' \xi(\theta^d),$$

where Z is a matrix of instruments and $\hat{W}$ is a consistent estimate of the optimal weight matrix obtained from a first stage estimate. This estimator is asymptotically normal with variance covariance matrix provided in Berry, Levinsohn, and Pakes (1995) and Nevo (2000). For the instrument set, we use characteristics of competing models, a dummy for whether the model has a domestic assembly location, the tariff rate of the closest assembly location, the number of production locations interacted with a market dummy, and the minimum distance to an assembly location interacted with a market dummy.[19]

4.2 Demand Estimates

The demand estimates are presented in Table 8. Estimates of the tastes for characteristics are listed by country across columns at the top of table, with estimates of the standard deviation of the linear coefficients in the final column. Estimates of price sensitivity are provided at the bottom of the table. The price sensitivity parameters are all strongly significant and indicate that price sensitivity is decreasing in income ($\pi_\alpha < 0$) with substantial dispersion conditional on income (σ_α). This finding is consistent with Fieler (2011) who also estimated non-homotheticity in a general

[19]Results are robust to alternative specifications of the instruments.

Table 8: Parameter estimates for the demand model

Variable	Estimate									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA	R.C. Std
HP per Weight	0.783	0.102	0.348	0.484	-0.305	0.779	0.364	0.237	0.282	0.008
	(0.754)	(0.195)	(0.178)	(0.205)	(0.439)	(0.256)	(0.103)	(0.171)	(0.134)	(0.023)
HP per Weight^2	-0.023	-0.000	-0.004	0.000	0.045	-0.017	-0.006	-0.004	-0.005	
	(0.043)	(0.008)	(0.005)	(0.006)	(0.025)	(0.012)	(0.004)	(0.007)	(0.004)	
Size	3.928	10.424	8.169	4.916	9.579	8.488	7.757	7.369	6.601	0.095
	(2.688)	(2.920)	(1.616)	(1.779)	(2.089)	(1.914)	(1.909)	(1.766)	(1.303)	(0.158)
Size^2	-0.037	-0.465	-0.350	-0.100	-0.445	-0.387	-0.343	-0.333	-0.312	
	(0.185)	(0.168)	(0.083)	(0.101)	(0.126)	(0.105)	(0.107)	(0.104)	(0.073)	
Miles per Dollar	1.055	-2.273	0.077	2.927	1.600	0.744	-0.706	-2.501	-2.070	0.142
	(0.761)	(0.782)	(0.289)	(0.832)	(0.538)	(0.612)	(0.680)	(0.788)	(0.491)	(0.158)
Miles per Dollar^2	-0.065	0.179	-0.001	-0.227	-0.141	0.001	0.067	0.273	0.086	
	(0.046)	(0.071)	(0.015)	(0.082)	(0.041)	(0.059)	(0.059)	(0.080)	(0.024)	

Price Sensitivity Parameters

	$\overline{\alpha}$	π_α	σ_α
Price	9.434	-0.709	1.003
	(1.803)	(0.173)	(0.209)

Notes: The units for HP per weight, size, and price are horse power per 100 kg, m^2, and 10 thousand dollars, respectively. This specification uses brand-country dummies. Weighted bootstrap standard errors in parenthesis.

Table 9: Home preference estimates

Variable	I	II	III	IV
Home Preference, ρ	1.136	1.013	0.804	0.745
	(0.092)	(0.094)	(0.096)	(0.082)
Years in Market		0.005		0.003
		(0.002)		(0.001)
Dealer Density			0.178	0.169
			(0.024)	(0.014)

Notes: Home preference assumed to be homogeneous across countries. Weighted bootstrap standard errors in parenthesis.

equilibrium trade model using aggregate data.

Considering taste for size, all countries have a positive linear and a negative quadratic coefficient (implying decreasing marginal utility) that are significant for seven out of nine countries. At the median size, consumers have positive marginal utility for size in all countries. Taste for horsepower is typically positive and appears close to linear, although it is statistically insignificant. Taste for miles per dollar is most heterogeneous across countries: consumers from the United States seem to value miles per dollar much less than French and German consumers. Some countries' median consumer has a distaste for miles per dollar, which may arise due to collinearity with other characteristics. Looking across countries and characteristics, Canada, Italy and the United States are remarkably similar in their tastes, while there are substantial differences between other countries. The random coefficients for non-price characteristics are insignificant and smaller in magnitude, suggesting that within market taste heterogeneity is largely captured either through price sensitivities or in mean differences across countries.

Consumers may also have an innate preference for purchasing local brands. For example, one might expect that Germans prefer Volkswagen because they view it as a German brand, while Italians might derive extra utility from purchasing a Fiat. The brand country dummy estimates, $\widehat{\psi}_{mb}$, capture revealed tastes for particular brands within country m. These will include whether or not a brand is considered a "home brand" by consumers, as well as the unobserved quality of the brand (such as reliability), its marketing cachet, the availability of dealerships and repair shops for the brand, et cetera. To assess the strength of home preference in brands, we project the brand market fixed effects on whether or not a brand is domestic, a series of brand-market level controls, as well as brand and market fixed effects. Specifically, we follow Chamberlain (1982) and Nevo (2001) to estimate,

$$\widehat{\psi}_{mb} \;=\; \rho\mathbf{1}[b \text{ is a domestic brand in } m] + \gamma w_{mb} + \eta_b + \mu_m + u_{mb}, \tag{10}$$

where ρ represents the home market preference. Brand fixed effects control for the overall quality of the brand, while the controls, w_{mb}, account for brand market characteristics which are likely to be correlated with home status. We include a measure of brand history in a market —the number of years the brand has been operating in the country prior to the start of our data—and a measure of convenience for the consumer—the number of dealerships per capita that sell the brands' products.[20] We refer to the parameter of interest, ρ, as home preference; it is the revealed preference for buying home brands, after controlling for characteristics of offerings, overall brand quality, and the brand history and dealer network in a market. This preference may have several sources, including: the ability of home brands to provide unobserved characteristics that better fit their home market, consumers' nationalistic feelings for domestic brands, or consumers' stronger familiarity with domestic brands.

Table 9 presents our estimates of the drivers of brand preference varying the set of controls. Across all specifications, the home preference estimate is substantial and highly significant. The impact of history and dealer density attenuates the estimate of home preference by up to 35 percent, suggesting that the head start of national brands plays an important role in their dominance.[21] For our preferred specification with both controls in column IV, the median consumer's willingness to pay for a domestic brand ranges from about \$800 US (in Spain) to about \$1,050 US (in Germany).

To investigate how home preference varies across countries, we also estimate the model allowing ρ and γ to be interacted with market country. The results, presented in Table 10, show that the home preference is not driven by outlier countries. Because most countries have relatively few home brands, these estimates are less precise, although most estimates remain statistically significant. However, there is some heterogeneity in home preference across countries. We find that home preference is highest in Spain, France, and Italy. The countries with the smallest home preferences

[20] While the number of dealerships changes slightly from year to year, it is highly persistent so we fix it over our time in our data and rely on cross-brand variation. See the data Appendix A for details.

[21] This result is robust to alternative specification of market-brand characteristics, such as rank of entry (rather than years in market) and including controls in logarithms (as opposed to levels).

Table 10: Country-specific home preference estimates

	I	II
DEU	0.812	0.212
	(0.193)	(0.286)
ESP	1.489	1.350
	(0.697)	(0.704)
FRA	1.533	1.296
	(0.211)	(0.262)
GBR	1.455	0.978
	(0.224)	(0.216)
ITA	1.712	1.094
	(0.304)	(0.303)
USA	0.645	0.177
	(0.159)	(0.199)
Brand controls	No	Yes

Notes: Home preference and controls (for column II) are heterogeneous across countries. Weighted bootstrap standard errors in parentheses.

Table 11: Median own and cross-price elasticities for select models

	Audi A6	Ford Focus	Mercedes E350	Renault Clio	Toyota Corolla
Audi A6	-6.475	0.017	0.124	0.002	0.010
Ford Focus	0.036	-10.756	0.020	0.232	0.323
Mercedes E 350	0.065	0.004	-6.035	0.002	0.001
Renault Clio	0.004	0.280	0.001	-11.346	0.032
Toyota Corolla	0.002	0.380	0.001	0.270	-11.478

Notes: This table shows the substitution elasticity of models in the row with respect to the prices of models in the column. Each entry represents the median of elasticities across country-years.

are Germany and the United States. These results are consistent with the findings of Goldberg and Verboven (2001a) who find a strong preference for domestic brands in European car markets between 1980-1993.

4.3 Elasticities and Markups

The demand parameters directly imply elasticities and markups for each model. In Table 11 we present the elasticities and cross-elasticities for selected models in the subset of markets where these models compete. Looking at the own-price elasticities, we see they vary in an intuitive way.

Table 12: Median markups of select models across years (percent)

	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
Audi A4	13.3	17.4	17.4	20.6	21.2	23.0	19.7	21.8	16.1
Audi A6		20.4	21.6	22.6	23.2	25.7	20.8	23.6	23.1
BMW 530		21.3		19.7	23.2	25.7	21.6	23.5	22.4
BMW X3		18.5	17.6	18.0	20.3	23.6	20.0	21.2	20.0
Chrysler 300		16.0	16.0	15.1	17.1	20.6	16.6	17.0	16.4
Ford Fiesta	9.1	7.9		12.5	13.0	11.8	12.0	11.6	10.8
Ford Focus	11.5	8.8	9.8	10.7	12.7	12.8	12.5	13.6	10.0
Honda Accord		11.9	13.9	11.5	16.2	17.4	15.0	15.7	12.8
Honda CR-V	14.3	11.7	14.9	11.8	16.1	17.7	14.7	16.2	12.2
Jaguar XF		19.1	21.0	16.5	21.5	22.9	21.1	19.8	23.9
Jeep Grand Cherokee		17.4	18.8	15.8	18.8	21.3	17.4	18.2	18.4
Lexus RX 450		21.8	24.0	19.0	24.5	25.9	21.0	21.6	24.8
Mercedes E 350		21.4	21.5	20.3	23.0	24.9	20.4	21.8	23.9
Mini New Mini	13.3	8.6	10.4	10.8	12.3	12.7	10.6	13.9	9.3
Renault Clio	7.8	8.8		12.4	14.0	15.8	11.3	11.2	
Toyota Corolla	12.0	8.3	11.6	10.8	12.1	11.3	8.7	10.4	11.1
Toyota RAV-4	13.8	12.1	13.3	11.9	15.6	17.0	14.6	16.1	12.4
VW Golf	11.9	11.5	9.5	17.1	17.0	15.4	14.3	16.2	10.1
VW Passat	13.4	14.6	13.1	19.7	19.4	19.8	16.1	20.3	13.6
VW Tiguan	13.3	15.5	13.4	19.0	20.4	20.5	17.9	20.4	13.0

The luxury models are are the least elastic while the three compact-to-midrange models are more elastic. The Toyota Corolla, which is never a home-brand in our market, has the highest median own-price elasticity. When we consider the cross-elasticities, the table illustrates that the model is able to capture the expected competitive patterns. The two luxury models, the Audi A6 and Mercedes E350, compete most strongly with each other, although the cross elasticities in the luxury class are generally smaller than for more quotidian models, suggesting that price competition is less fierce in in the luxury portion of the market. Similarly, Renault Clio, Toyota Corolla, and Ford Focus compete strongly with each other but not with the luxury vehicles.

Our estimates of elasticities directly predict markups according to the firm's first order condition (8). Table 12 presents the median (across years) of the implied markups for a selection of models in all countries where those models appear. Intuitively, markups are lowest in Brazil, which is by far the lowest income country in our data set. The highest markups tend to be found in France, with Spain and Italy close behind. Looking across brands, luxury cars, such as the BMW 530 and Mercedes E 350, tend to have the highest markups. Several smaller model such as the VW Golf,

Table 13: Weighted average markups of manufacturers across markets (percent)

	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
Fiat	10.8	8.6		11.8	10.7	12.4	10.9	16.8	8.7
Ford	9.5	9.7	13.1	11.9	11.6	12.9	12.8	12.6	13.3
GM	10.4	9.5	13.6	12.1	12.0	12.8	12.6	12.6	15.4
PSA	10.2	10.6		11.7	13.1	18.4	11.5	12.6	
Toyota	12.3	9.7	13.0	11.7	12.1	13.6	11.9	11.9	14.0
VW	10.7	12.9	12.6	18.6	15.5	16.6	15.3	16.6	14.0

Mini, and Ford Fiesta tend to have smaller markups in the United States than they do in European countries. SUVs such as the VW Tiguan command high markups in Europe and lower markups in the United States and Canada, where they face significantly more competition. Overall, the model produces intuitive estimates of markups—and hence marginal costs—across countries and models.

To illustrate differences between markups for domestic and foreign products, Table 13 presents weighted average markups aggregated to the firm-country level. Across the table, we see that firms tend to charge their highest markups in their home countries. Volkswagen in Germany, Ford and General Motors in the United States, and most strikingly PSA (Peugeot Citroen) in France and Fiat in Italy. The pattern of home country markups relative to markups of the same firm in other countries is consistent with demand drivers playing an important role for home market advantage.

4.4 Supply Parameterization and Estimation

In the second stage of our estimation procedure, we use the costs implied by the demand model to estimate the supply side using nonlinear least squares. To do so, we parameterize $c_1(h_{jmt}, \kappa)$ and $c_2(g_{jm\ell t}, \delta)$, which determine the costs associated with selling model j in market m and the costs associated with sourcing model j from assembly location ℓ, respectively.

For country-model-specific costs, we assume,

$$\begin{aligned} \log c_1(h_{jmt}, \kappa) \; &= \kappa^{hp} \; \log \mathrm{hp}_{jmt} + \kappa^{wt} \; \log \mathrm{wt}_{jmt} + \kappa^{sz} \; \log \mathrm{size}_{jmt} \\ &+ \kappa^{mg} \; \log \mathrm{mpg}_{jmt} + \kappa^{mt} + \kappa^{j}. \end{aligned} \tag{11}$$

As opposed to the demand side, we allow costs to be determined by horsepower and weight separately, rather than by their ratio. This is intuitive because we would expect both to increase the cost of a car, whereas on the demand side we were using their ratio as a measure of acceleration while accounting for size separately. We also include miles per gallon (mpg)—rather than miles per dollar—on the cost side. This is because the price of gas in m should affect demand for fuel-efficient vehicles, but not the cost of producing fuel-efficient vehicles. Finally, the supply side includes market country, time and model fixed effects. In contrast, the demand side includes brand-country effects. We prefer this specification because it allows us to control for the substantial variation in unobserved costs of models within brands on the supply side while being flexible about how tastes for brands vary across countries on the demand side.[22] Even when we include a set of model fixed effects on the supply side, the effect of characteristics on cost are still identified due to variation in the characteristics of a model both across countries and across years.

The final element of the supply side is the assembly location specific cost function $c_2(g_{jm\ell t}, \delta)$,

$$\begin{aligned} \log c_2(g_{jm\ell t}, \delta) = & \delta^{mdist} \log \mathrm{dist}_{m\ell} + \delta^{dom} \mathbf{1}[\ell = m] + \delta^{ctg} \mathbf{1}[\ell \text{ is contiguous to } m] \\ & + \log(1 + \delta^{trf} \cdot \mathrm{tariff}_{m\ell t}) + \delta^{hqdist} \log \mathrm{dist}_{h(j)\ell} + \delta^{xr} \log \mathrm{fxrate}_{\ell t} + \phi_\ell. \end{aligned} \tag{12}$$

The first three terms capture the effect of trade costs, including a direct effect of distance as well as dummies to control for domestic and contiguous trade, in a traditional iceberg-like fashion.[23]

The parameter δ^{trf} captures the proportion of the model's cost subject to import tariffs.[24] Import tariffs are *ad valorem* based on the reported port cost of the car, which is likely to be lower than the marginal cost of the car implied by profit maximization, since the latter includes internal shipment and marketing costs. Below, we estimate the model both holding δ^{trf} fixed at one (the case where tariffs are paid on the full marginal cost) and allowing it to be estimated.

The next term, $\delta^{hqdist} \log \mathrm{dist}_{h(j)\ell}$, accounts for the impact of distance between a firm's headquarters and the assembly location. Costs may be larger for distant plants due to monitoring or communication costs between a headquarters and its plants, or due to shipment of intermediate

[22] We have also estimated several alternative specifications, including model fixed effects on both demand and supply sides and country-brand effects on both sides. The results are qualitatively similar.

[23] Recall that we use internal distance when the assembly and market countries are the same ($m = \ell$), see footnote 8 in Section 2 for details.

[24] While identification comes mainly from the cross-section, there is also time variation in tariffs due to several types of events during the data period: some assembly countries become a member to the World Trade Organization (Ukraine's entry in 2008), the EU and US reclassify countries in their Generalized System of Preferences and finally free trade agreements come into force (EU-Korea FTA in 2011).

inputs.[25] The second to last term, $\delta^{xr} \log \text{fxrate}_{\ell t}$ captures the effect of exchange rate variation in source locations to costs. $\text{fxrate}_{\ell t}$ is local currency per USD, normalized to one for the base year 2007. A depreciation of assembly country currencies would decrease dollar costs if $\delta^{xr} < 0$. Finally, we control for productivity differences across assembly locations with a location fixed effect, ϕ_ℓ, that is common to all plants within a country. This term absorbs both productivity difference across assembly countries and measurement error of internal distances within the assembly country.

The vector of supply parameters to estimate is $\theta^s = (\kappa, \delta, \phi, \sigma_\nu)$. The estimator for the supply side is the minimizer of the nonlinear least squares objective function,

$$\hat{\theta}^s = \underset{\theta^s}{\operatorname{argmin}} \sum_{m=1}^{M} \sum_{t=1}^{T_m} \sum_{j=1}^{J_{mt}} \omega_{jmt}(\theta^s)^2,$$

where,

$$\omega_{jmt}(\theta^s) = \log \hat{c}_{jmt} - \log c_1(h_{jmt}, \kappa) + \sigma_\nu \log \left(\sum_{k \in L_t(j)} \exp\left(\frac{-\log c_2(g_{jmkt}, \delta)}{\sigma_\nu} \right) \right).$$

To account for the fact that marginal costs $\hat{c}_{jmt}$ are functions of demand estimates, standard errors are calculated using a weighted bootstrap.

In practice, we find that the objective function is minimized at low values of $\hat{\sigma}_\nu$, indicating that the gains to variety are very small. For such values of σ_ν, the probability of sourcing from any particular location converges to either one or zero depending on whether that location is the minimum cost supplier or not. At low values of σ_ν, model predictions about marginal costs become insensitive to variation in σ_ν. As a result, the objective function becomes almost flat in this region, although other parameters are precisely estimated. Therefore, we fix $\bar{\sigma}_\nu = 0.01$ and estimate the remaining parameters of the model.[26] A low estimate of σ_ν is consistent with the findings of Head and Mayer (2015), who report that at the model level, firms almost always source a specific market from a single origin country.

Table 14: Cost estimates

Variable	I	II	III	IV
Horsepower, κ^{hp}	0.277	0.277	0.299	0.299
	(0.041)	(0.041)	(0.041)	(0.041)
Weight, κ^{wt}	0.172	0.171	0.174	0.173
	(0.033)	(0.032)	(0.033)	(0.033)
Size, κ^{sz}	0.331	0.331	0.331	0.332
	(0.016)	(0.016)	(0.016)	(0.016)
Miles per Gallon, κ^{mg}	0.036	0.036	0.036	0.036
	(0.012)	(0.012)	(0.012)	(0.012)
Assembly to Market Distance, δ^{mdist}	-0.002	-0.002	0.015	0.015
	(0.004)	(0.004)	(0.004)	(0.004)
Domestic Location, δ^{dom}	-0.019	-0.020	-0.003	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Contiguous Location, δ^{ctg}	-0.011	-0.011	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Assembly to HQ Distance, δ^{hqdist}	0.004	0.004	0.009	0.009
	(0.008)	(0.007)	(0.006)	(0.006)
Tariff, ζ			0.697	0.697
			(0.076)	(0.075)
FX rate, δ^{xr}		-0.010		-0.017
		(0.015)		(0.015)
Fixed σ_ν	0.01	0.01	0.01	0.01

Car cost, distance measures, tariff, and car characteristics are in logarithm. Weighted bootstrap standard errors in parentheses.

4.5 Supply Estimates

The estimates of the supply side are presented in Table 14. Considering the effect of characteristics on the cost side (top panel), horsepower, size, weight and fuel efficiency all have the expected sign and are statistically significant. Turning to sourcing related costs (bottom panel), we find that for our preferred specification (column IV), production at a domestic (δ^{dom}) or contiguous-country (δ^{ctg}) plant decreases costs. The cost elasticity of distance, δ^{midst}, is comparable the estimate of Head and Mayer (2014) (0.036) and within the range of estimates summarized by Head and Mayer (2013). It is slightly lower than the estimate from the reduced form price regression in Table 7, which could be interpreted as a cost elasticity under the assumption of perfect competition where firms always source from the nearest location. Assembly-to-HQ distances (δ^{hqdist}) increase

[25] See Giroud (2013) and Tintelnot (2014) for a discussion and evidence for such frictions.

[26] The estimates and counterfactual results are robust to fixing σ_ν within a range of [0.001,0.2]. Moreover, an LR-type test rejects $\sigma_\nu > 0.2$ at the 95% confidence level.

marginal costs, suggesting that there are non-trivial monitoring and management costs related to remote production. This effect is smaller than the assembly to market cost elasticity and is not statistically significant.

We also find, however, that properly controlling for tariffs matter for the magnitude of these effects. In Columns I-II, the tariff incidence parameter, δ^{trf}, is fixed at one—so the tariff applies to the full marginal cost of the car—and in Columns III-IV, we allow δ^{trf} to be estimated. When estimating δ^{trf}, we find that it is significantly below one, implying that the tariff is applied to less than the full marginal cost of the car, consistent with the presence of a portion of marginal costs being to do destination-specific internal delivery and marketing. Estimating δ^{trf} also has a substantial effect on the estimates of trade costs. In particular, the cost of assembly-to-market distance (δ^{mdist}) has the expected sign and statistical significance only when tariffs are controlled for (from column II to III). In reverse, the benefits of being domestic and contiguous both decrease and lose significance. This is intuitive because tariff rates are positively correlated with distance. Tariffs are naturally zero when the assembly plant is domestic and tend to be low between contiguous countries due to regional trade agreements. As a consequence, fixing the tariff incidence parameter above its estimated value induces downward bias on the impact of distance and an upward bias on the benefits of domesticity and contiguity. The exchange rate parameter δ^{xr} in columns II and IV is negative as expected, though small in magnitude (a 10 percent depreciation of the assembly country currency would decrease total production costs – which includes costs incurred in the assembly, market, and possibly other supplier countries – by about .17 percent). From column III to IV, its inclusion does not significantly alter other estimates.

Our model delivers implied trade flows between countries at the model level through (3) and (4). We use this to conduct an out-of-sample test of our cost estimates by investigating how well they match aggregate trade flows. Specifically, we aggregate model-level flows up to the country-pair level and compare them to trade flows reported in the WITS database of the World Bank.[27] Figure 1 presents the scatter plot comparing our implied trade flows (in logs) with those in the trade data together with the best linear predictor of the data given our model flows. If our model

[27] This data is trade flows reported by importers in HS6 product categories associated with assembled cars. These HS product codes are: 870321, 870322, 870323, 870324, 870331, 870332, 870333, and 870390. This data includes many small flows due to personal imports of automobiles, so we exclude pairs with less than \$5 million in reported flows, which amounts to roughly 200 units, the reported results are robust to adjusting this cutoff.

perfectly replicated the aggregate data, the estimated slope of this regression would be exactly one, and R^2 would be one. In fact, the regression estimates a slope of 0.71 and the R^2 of this regression is 0.38. There are many reasons why we fail to match the aggregated trade flows perfectly. Our costs are not intended to represent the costs at importing, but are instead the marginal costs the firm uses for setting prices—including costs incurred internal to the market country. Moreover, there is likely measurement error in both the aggregated trade flow data and in our data on market shares and prices used to estimate our model.[28] Finally, some mis-specification of our parametric functional forms used in estimation is inevitable. Overall, we believe the fact that the implied flow data matches the aggregate data as well as it does provides some degree of confidence that the model is capturing the essential drivers of market outcomes.

4.6 Trade and Foreign Production Frictions

To get a sense for the magnitude of the estimated trade frictions, we conduct two exercises which calculate the proportion of automobile costs that are due to external shipping and remote production, and showcase how these quantities vary across brands and countries. Note that this analysis computes costs actually paid in overcoming production frictions. It is not able to capture the impact of production frictions which firms endogenously avoid (e.g., sourcing locally to avoid

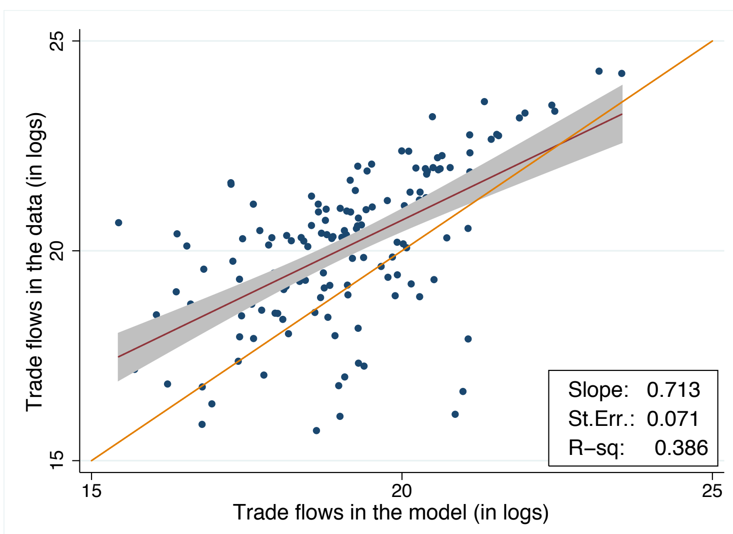

Figure 1: Predicted trade flows and data

[28]Moreover, our model prices, shares and characteristics are themselves aggregations of finer trim-level data on new automobile sales.

Table 15: Weighted average external shipping cost (percent of marginal cost)

	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
Fiat	0.0	4.8		2.3	2.7	2.2	3.8	1.2	2.5
Ford	0.2	3.9	0.7	2.2	3.3	2.5	4.1	3.3	0.2
GM	0.2	4.0	0.6	1.3	2.2	1.9	1.7	2.1	0.2
PSA	0.4	4.4		2.2	1.5	1.5	3.2	2.3	
Toyota	0.3	6.0	0.9	3.8	3.9	3.3	4.3	3.8	1.1
VW	0.2	3.7	2.5	1.1	1.4	1.8	2.9	2.0	1.6

market to avoid high tariffs and shipping costs). In the following section, we conduct a series of counterfactuals which allow firms to re-optimize production decisions when frictions are removed.

Table 15 reflects the percentage of the total cost that is directly related to external shipping, domesticity, and contiguity. In this exercise, we use the estimates from column IV of Table 14 to calculate the proportion of costs paid which are due to shipping from an international location. That is, we calculate the change in total costs when we set the domestic dummy equal to one, the contiguity dummy equal to zero, and the distance between the assembly countries and the destination market equal to the internal distance of the destination market. This calculation keeps tariffs, sourcing locations, and the distance between assembly and headquarters the same. We see some variation by firm and country, ranging between 0 percent (Fiat in Brazil) to 6 percent (Toyota in Belgium) of the marginal cost. As we would expect, these costs tend to be relatively low in the firm's home country, despite the fact that even home firms import at least some proportion of their cars from abroad, generating positive external shipping costs. However, in Brazil, where many firms have local plants targeting South American markets, average shipping costs are actually lower as a share of costs than in home countries.[29]

Table 16 carries out a similar exercise by computing the proportion of costs due to sourcing from assembly locations outside the firm's headquarter country. In this case, we compute the proportion of additional costs from assembling cars outside of the home headquarter country as a proportion of the overall cost. Not surprisingly, these costs tend to be smallest in the firm's home country, although they are not zero since, again, firms source some models in home markets from abroad. These costs range from about 0.1 to about 3.5 percent of marginal costs of supplying a model to a

[29] It is also interesting to note that General Motors has its lowest average shipping costs to European markets in Germany, where its Opel subsidiary is based.

Table 16: Weighted average remote production cost (percent of marginal cost)

	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
Fiat	2.8	0.8		1.1	1.1	1.0	1.3	0.7	1.7
Ford	1.4	1.1	0.1	1.0	0.9	1.2	1.0	1.1	0.1
GM	1.3	1.3	0.1	1.3	1.3	1.3	1.3	1.4	0.1
PSA	2.8	0.9		1.0	0.9	0.9	1.1	1.2	
Toyota	3.5	1.7	2.6	1.8	1.5	2.0	1.7	1.9	2.0
VW	3.1	0.8	2.2	0.6	1.1	0.9	0.9	0.8	2.0

market. As with shipping costs, the case of Brazil is especially interesting since remote assembly costs tend to be highest there. This is the flip side of the low shipping costs for the Brazilian market observed in Table 15. Firms are endogenously choosing to locate assembly locations in Brazil, incurring remote production costs instead of paying higher shipping costs and high import tariffs to access the Brazilian market.

5 What Drives Home Market Advantage?

In Section 2, we illustrated that firms tend to have substantially larger market shares in their home market. In Sections 3 and 4, we proposed and estimated a structural model that accounts for various demand and supply channels that could generate this home market advantage. These include tariffs, trade and remote production costs, cross-country heterogeneity in tastes for characteristics, and a preference for domestic brands. In this section, we use these estimates to asses the role of each in contributing to the home market advantage.

To do so, we re-estimate the same regression across a series of counterfactuals:

$$\log(s_{jmt}) = \lambda \cdot \mathbf{1}[b(j) \text{ is a home brand in } m] + \alpha_j + \gamma_{mt} + \varepsilon_{jmt}, \tag{13}$$

where the parameter λ measures the extent of "home market advantage." We do not interpret λ causally, but instead use it as a metric of how home brands correlate with higher market shares in the data. At the structural estimates, prices and market shares exactly match the data, so the results from this exercise under the baseline are equivalent to our preliminary analysis in Section 2 (Table 4, Column 3), which implies that being a home brand implies a 238 percent increase in market share over equivalent foreign brands. For each counterfactual, we recalculate equilibrium costs, prices, and market shares, holding fixed model offerings within each market and the set of available assembly locations for each model.[30] However, we allow firms to re-optimize their sourcing decisions from this set. Therefore, these counterfactuals should be interpreted as "medium run" in the sense that firms can adjust sourcing and prices, but neither the entry/exit of models into markets, nor the construction/closure of assembly plants. Using these counterfactual market shares, we re-estimate (13) to determine the change in the home market advantage. Clearly, some of these counterfactuals do not represent changes that are achievable via policy. However, our goal is to use them as thought experiments to illustrate the drivers of home market advantage.

Table 17 displays the results. The first column reports the estimated coefficients under each counterfactual. The second column reports the implied change in the market share difference between the baseline and the counterfactual estimate of λ. We now discuss each of the scenarios in turn.[31]

Supply We begin by examining supply side explanations for the home market advantage. In general, we would expect trade and foreign investment decisions to lead to cost differences that favor home brands. However, we do account for the fact that some brands (particularly in Europe) do assemble models abroad for the home market. Nonetheless, the home market advantage declines in all of our scenarios where we remove supply side frictions.

We first consider the removal of all tariffs on automobile trade. This results in a slight decline in home market advantage of 4 percent. One reason for this is that many popular models of foreign brands are either produced domestically or in countries where tariffs are already low—if not zero—due to regional free trade agreements. As a result, eliminating tariffs has only minor effect on costs, which feeds through to a small decline in home market advantage. We get a stronger effect when we remove international trade frictions from the model—reducing shipping costs to their domestic level regardless of location. This results in a 11.8 percent decline in the home market advantage, the largest individual effect we find on the cost side. This counterfactual both reduces

[30] As is well known, discrete choice demand models with consumer heterogeneity in tastes for characteristics and price could have multiple equilibria in the pricing game. We have not found such multiple equilibria for our estimates, but we also cannot rule out that they occur. We use the iterated best response algorithm starting from the initial equilibrium in order to compute the new equilibrium.

[31] We present brand-country level market shares under each counterfactual in Appendix B. Price and profit outcomes are available from the authors by request.

Table 17: Home market advantage under counterfactual scenarios

	Coefficient λ	Home Market Advantage (% Chg)
Baseline	1.22	
Supply:		
All tariffs eliminated	1.19	-4.0
No international trade frictions	1.13	-11.8
No multinational production frictions	1.21	-1.1
No tariffs, trade or multinational production frictions	1.12	-12.9
Demand: Taste Heterogeneity for characteristics		
All countries have French tastes for characteristics	1.19	-4.0
All countries have US tastes for characteristics	1.36	21.0
All countries have German gas prices	1.23	1.3
Demand: Home Preference		
No home preference, homogeneous	0.63	-62.9
No home preference, country-specific	0.72	-55.6
No home preference, homogeneous, no local controls	0.32	-84.3

Notes: Change in market share gap is calculated following Kennedy (1981) and van Garderen and Shah (2002), see footnote 7 for details.

shipping costs directly and allows firms to reallocate production to remote but productive assembly locations. Removing the remote production friction from the model–eliminating costs associated with the distance between assembly plants and headquarters location—has only a small effect on home market advantage, which declines by 1.1 percent. It is interesting that this effect is less than one-tenth the magnitude of that from removing trade frictions. Overall, when we remove all cost-side frictions, the home market advantage estimate declines by 12.9 percent. This suggests that cost-side drivers are an important but far from complete driver of home market advantage.

Taste heterogeneity for characteristics The impact of cross-country taste heterogeneity on home market advantage is complex. While one might expect firms to produce cars with their home market foremost in mind, firms can also customize model offerings as appropriate. This activity is pervasive, as illustrated by Table B.1, which shows that all manufactures, regardless of origin, sell larger, more powerful, less fuel-efficient cars in the United States than they do in Europe. Moreover, firms may target different segments abroad than they do at home. US manufacturers tend to sell smaller, more fuel-efficient cars in European countries than German manufacturers, forgoing the large cars (mostly SUVs) that they choose to offer in the United States.

Because of the complexity of model offerings across countries, a harmonization of characteristics for tastes can have an ambiguous effect on home market advantage in the medium run, depending on how tastes are harmonized. To illustrate this, we conduct two counterfactuals where we harmonize tastes in different ways by endowing all countries with the tastes of the United States and France – two countries whose tastes differ dramatically with regard to fuel economy – as well as a third counterfactual in which we harmonize gas prices in all countries to German prices, where gas is the most expensive. Predictably, imposing US tastes on other countries leads to an increase in the share (and profits) of fuel-inefficient cars, whereas imposing French tastes on the US leads to an increase in the share of fuel-efficient cars (see Appendix Table B.6). However, the brands that benefit in these experiments differ dramatically across countries. Imposing US tastes leads to a dramatic increase in the share of *German* brands—who tend to offer less fuel-efficient vehicles—in all countries except Brazil and the US. On the other hand, US brands—who tend to offer more fuel-efficient cars abroad than at home—lose market share in all countries except Canada (and of course the US). Similarly, the impact of harmonizing tastes to be as those in France primarily benefits Japanese firms, who tend to offer relatively fuel efficient cars in all markets. As a result, we find that the home market effect can either be exacerbated or reduced by harmonizing characteristics *depending on how they are harmonized*. In the cases presented here, imposing US tastes increases the home market advantage by 21 percent (largely due to the experience of US brands) while imposing French tastes decreases it by 4 percent. Raising gas prices to the German level doesn't have a big impact since gas prices show little variation within Europe. In the US, however, Japanese and Korean makers of fuel-efficient models gain considerable market share at the expense of American producers (bottom panel of Table B.4—Korean makers are in the "Other" category). European producers also lose some market share since their product portfolio in the US market features relatively larger models, plausibly in response to the cheaper price of gas.

Of course, like all our counterfactuals, these results represent a medium run approach where firms cannot adjust product offerings. In the long run, firms would plausibly adjust their product assortment in response to such dramatic changes in local tastes. Their ability to do so would depend on the costs of customization. Estimating costs of customization would require a dynamic model of equilibrium product characteristics (Eizenberg, 2014; Wollmann, 2014). High adjustment costs would suggest a greater role for taste heterogeneity for home market advantage in the long

Table 18: Value of domestic brand status for selected brands

	Percent Change in		
	Price	Quantity	Profit
Seat in Spain (VW)	-0.8	-69.6	-71.9
Vauxhall in UK (GM)	-1.1	-53.6	-58.1
Chrysler in US (Fiat)	-0.1	-14.0	-14.3
Opel in Germany (GM)	-0.2	-13.8	-15.1
VW in Germany	-0.4	-12.1	-14.2
Renault in France	-2.1	-60.7	-66.4
Fiat in Italy	-2.2	-50.5	-58.5
Chevrolet in US	-0.2	-12.8	-14.2

run. However, the fact that firms do customize their product portfolios across markets, rather than naively offer products that are popular at home, suggests that these customization costs are not extreme. This cuts against the argument that taste heterogeneity is a key driver of home market advantage in the long run, at least in the automobile industry.

Home preferences Finally, we remove consumers' direct preference for home brands by eliminating the structural home preference. The final panel of Tabel 17 presents this calculation using two specifications, either treating the home preference as homogenous across countries (Table 9, Column IV) or as country specific (Table 10, Column II). Either way, we find that eliminating home preference has a dramatic effect on the home market advantage, which falls 56 to 63 percent. Note that this calculation controls for the fact that home brands tend to have more dealerships and a longer history in their own home country. Not including these controls (Table 9, Column I) results in an even larger effect: reducing home market advantage by 84 percent. This leads us to conclude that demand-side effects, and home brand preference in particular, are the key channel that gives rise to home market advantage in the automobile industry in the medium run, while cost-side elements play a substantive but secondary role.

An interesting feature of the automobile industry is that there have been several mergers where an international firm owns a domestic brand but maintains its "domestic" image in marketing campaigns (e.g., Volkswagen ownership of SEAT in Spain, GM's ownership of Vauxhall and Opel in the UK and Germany, and Fiat's recent purchase of Chrysler in the United States). Our results suggest that one benefit of operating "domestic" brands for foreign firms is due to consumers' preferences for local brands. Hence home preferences can provide a motive for foreign direct investment (via acquiring local brands), analogous to jumping tariffs by establishing foreign production. To explore this idea in more detail, we use our model to calculate the importance of brand-nationality to the profitability of home brands. Specifically, we remove the home preference from only the brand under consideration and re-calculate the equilibrium to see the impact of home preference on that brand.[32] Table 18 reports how removing home preference affects local brands' prices, sales and profitability in their home country. The upper panel considers foreign-owned brands, while the lower panel lists the largest home brand in the country.[33] We find that home market advantage is extremely important to domestic brand's operating profits. Although firms do react to the loss of home preference by lowering prices slightly, the reduction in profits is largely due to a dramatic reduction in sales when the home preference is removed. The effect varies substantially by brand. The largest profit loss comes at the Spanish brand SEAT (72 percent), which is owned by Volkswagen but has a relatively small presence worldwide. Despite being foreign-owned, SEAT appears to actively cultivate a Spanish identity to the extent of offering models named the Leon, Toledo, and Alhambra. In contrast, Volkswagen itself—a strong worldwide brand—loses a comparably modest 14 percent of its local operating profits when its home preference is eliminated in Germany. In summary, the impact of home preference does appear large enough to suggest that buying a local brand may be an attractive mode of entry for foreign firms due to consumers' innate preference for local brands.

6 Conclusion

The automobile industry exhibits significant home market advantage in market shares. This paper proposes and estimates a structural model to disentangle the contribution of various demand- and cost-side elements to market outcomes. The estimates clearly establish the existence of both demand factors and supply frictions behind the empirical regularity of home market advantage. On the demand side, consumers exhibit strong preference for their domestic brands relative to how these brands are viewed in the rest of the world even after controlling for car and brand characteristics. Moreover, there are distinct differences in tastes for characteristics across countries. On the cost

[32]For this exercise, we use country-specific home preference estimates from Table 10.

[33]SEAT and Vauxhall are both foreign owned and the largest brand in their home country, so we do not repeat them.

side, tariffs, trade costs, and remote production costs all play a role in segmenting markets.

To establish the relative importance of these channels, we conduct a series of counterfactual experiments where we see how a common measure of home market advantage is affected by removing a particular feature of the model. We find that home preference is a major driver of the home market advantage, with an effect at least four times larger than removing all cost-side frictions. This, however, does not mean that other features are not important. In particular, our counterfactual analysis focuses on the medium run, while other factors could play a large role in determining how models are introduced into markets and where assembly locations are located.

Going forward, we believe this work opens up an exciting research agenda in the development of brand preferences in international markets. To this end, one needs a longitudinal analysis of how consumers' preferences evolve over time—such as inheriting preferences across generations (Anderson, Kellogg, Langer, and Sallee 2013)—and how firms invest in product development, distribution networks and marketing in response to these preferences in the presence of trade and multinational production frictions that segment markets.

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Appendices

Appendix A Data

A.1 Demand Data

We purchased a data set of trim-level unit sales, prices (MSRP) and characteristics (size, weight, horsepower, fuel type, transmission, wheel base) for nine markets (Belgium, Brazil, Canada, France, Germany, Italy, Spain, UK, US) and five years (2007-2011) from R.L.Polk & Company, a market research firm that got acquired by IHS Inc. in 2013. Data for the years 2007 and 2008 are missing for Brazil and Canada, respectively. Following the common practice in the literature, we aggregated sales to the model level since very small market shares at the trim level create numerical challenges for the BLP inversion. The aggregation used trim-level sales as weights to calculate average model prices and characteristics. We fill in the few cases of missing characteristics (most notably in Brazil), with the characteristics of the same models from the North American market. Prices at local currencies were translated into USD using the average annual exchange rate. This procedure generated 9498 observations. We dropped pickup trucks since they constitute a somewhat unique segment in the US. We also dropped observations for 2010-2011 in Canada since information on SUV models sold there in these years was missing. This leaves us with 8835 observations. Additional data comes from OECD (sales tax data) and the World Bank (per capita income, Gini coefficients).

A.2 Supply Data

To locate the production locations of unique model-year combinations in the demand data, we purchased data on assembly plants by manufacturer groups and models between 2007-2011 from Ward's Communications. Assembly countries for model-years present in the demand data but missing in the purchased supply data were collected by research assistants from the Internet. The complete supply data encompasses 52 assembly countries. The models produced in Uruguay belong to the Chinese brand Geely for which fuel efficiency measures are missing. As a result, we drop Uruguay as an assembly location. Also, data for Kenya and Bangladesh overlap in that Toyota Land Cruiser is the only model produced in these countries. Since this leads to multicollinearity in estimating model and production location fixed effects, we drop Bangladesh. This leaves us with 50 countries from which the models in the demand data could be supplied. The countries in which manufacturer groups are headquartered constitutes another dimension of the data, which is more easily accessible from online sources. There are 12 headquarter countries associated with the 28 manufacturing groups: China, Germany, Spain, France, the UK, Italy, Japan, Korea, Malaysia, Russia, Sweden and the US.[34] The CEPII dataset (Head and Mayer 2013) provides us with the distances between headquarter and assembly countries, as well as the distance and the contiguity of our nine markets to assembly countries. Bilateral tariff data come from TARIC (EU Integrated Tariff Database), Canada Border Services Agency, USITC and WITS databases. Most of the bilateral tariffs were constant throughout the data period with two exceptions. The entry of Ukraine to the WTO led to a reduction of US tariffs from 10% to the MFN level of 2.5%. EU tariffs to S. Korea decreased from 10% to 3% in 2011 when a free trade agreement became effective. We ignore

[34] For two manufacturing groups, Chrysler-Fiat and Renault-Nissan, we assigned each firm a separate headquarter country: Chrysler in the US and Fiat in Italy, Renault in France and Nissan in Japan. During this period, key managerial decisions at Chrysler were still made in Detroit and the merger of the two companies wasn't legally complete until 2014. Similarly, while the Renault-Nissan alliance coordinates on global procurement, production and marketing, they still keep their separate management structures and brand identities.

rules of origin requirements related to the regional value-added content in FTAs: for instance, according to NAFTA rules, a car can be imported from Mexico to the US tariff-free only if the regional value added content is above 62.5%. The rest is subject to tariff. Unfortunately, systematic model-level data on location-specific value-added is not available. In our cost estimation (subsection 4.5), we make an attempt to account for the fact that only a fraction of an imported car's cost is subject to import tariffs.

In order to investigate the sources of the brand-country fixed effects from the demand estimation, we supplement the demand data with information on brands' year of entry into and the number of their dealers in each of our 9 markets. The year-of-entry data was collected by consulting various sources including the Internet, business history books and companies' public relations agents. Data regarding the number of dealers was collected from Google Maps. There are 331 brand-country observations.

The number of car dealers for a manufacturer brand within a country is collected using Google Places API (`https://developers.google.com/places/webservice/search?hl=en`). This API provides a function called radar search that returns the search query given the key words, place types, center coordinates and radius of the area of interest. The query has detailed information including place id that can uniquely identify a place, coordinates and description. There is a limit for the number of results returned per search (200) and also the radius (50km). We set the keyword to be the name of manufacturer brand and the place type to be "car dealer".[35] Then we iterated over areas to cover the entire country by choosing different coordinate centers and set the radius to 50km. The area may cover places outside of the country, in which case we removed these results based on their coordinates. There may also be overlapped area search in the search iteration, and we removed the repeated results using place id. To avoid counting dealers of used cars, we did a radar search using used car as the keyword, and deleted a place if its id is found in the used car list.

Appendix B Additional Figures and Tables

The following tables present market shares from the baseline model (which exactly matches share and price data at the model level) and the counterfactual scenarios we consider. Data is aggregated according to brand nationality.

[35] Because Opel is a common place name in some countries, we use "Opel dealer" instead of "Opel" in the search where "dealer" is translated into the local language.

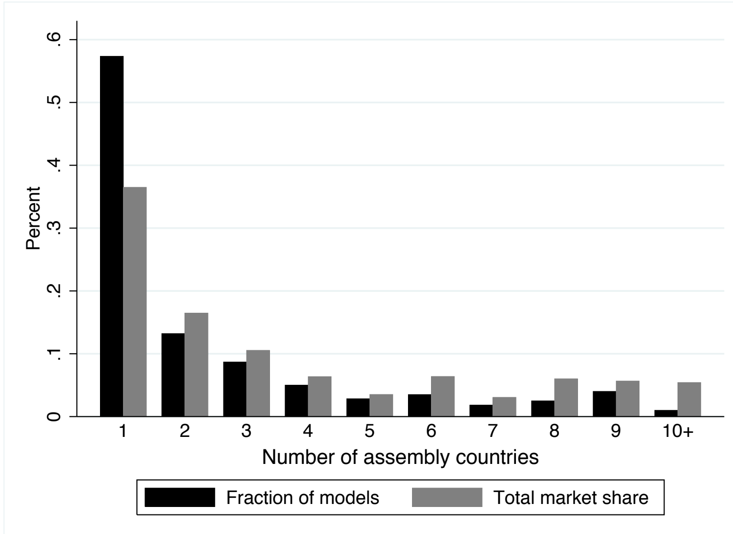

Figure B.1: Models and Market Shares by Number of Assembly Countries

Table B.1: Characteristics by Market

Variable	I	II	III
	$\ln(hppwt_{jmt})$	$\ln(size_{jmt})$	$\ln(mpg_{jmt})$
BEL	-0.276	-0.00876	0.251
	(0.00583)	(0.00118)	(0.00616)
BRA	-0.0444	0.00308	0.187
	(0.0111)	(0.00307)	(0.00830)
CAN	-0.000410	0.000774	0.0160
	(0.00572)	(0.00108)	(0.00546)
DEU	-0.195	-0.00600	0.155
	(0.00571)	(0.00106)	(0.00604)
ESP	-0.228	-0.00667	0.226
	(0.00573)	(0.00117)	(0.00613)
FRA	-0.239	-0.00648	0.265
	(0.00582)	(0.00113)	(0.00610)
GBR	-0.210	-0.00758	0.187
	(0.00581)	(0.00107)	(0.00618)
ITA	-0.235	-0.00840	0.227
	(0.00577)	(0.00111)	(0.00612)
Observations	8835	8835	8835
R^2	0.952	0.985	0.928
Year FE	Yes	Yes	Yes
Model FE	Yes	Yes	Yes

Standard errors in parentheses. US is the omitted dummy, so all coefficients showcase differences in country means against the US.

Table B.2: Data: average area-level market shares of brand nationality across markets (%)

Data/Baseline									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	31.2	8.9	34.1	8.3	11.3	6.6	15.9	11.6	39.6
EU brands	56.4	75.7	8.5	77.0	70.6	82.6	62.8	74.0	9.5
JPN brands	8.3	11.3	48.3	10.9	13.1	8.8	16.9	11.5	42.9
Other brands	4.1	4.0	9.1	3.7	5.1	2.0	4.3	2.9	7.9
Home brands				55.4	9.0	52.3	18.2	30.3	39.6

Table B.3: Supply counterfactuals: Average area-level market shares of brand nationality across markets (%)

No tariffs									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	26.7	10.1	29.7	9.6	13.0	7.0	18.5	13.6	37.3
EU brands	47.2	71.6	10.6	72.9	65.8	81.3	56.9	69.9	11.2
JPN brands	6.9	13.4	48.7	13.2	14.9	9.4	19.6	13.1	42.6
Other brands	19.2	4.9	11.0	4.3	6.2	2.3	5.0	3.5	8.9
Home brands				50.7	5.9	53.3	13.2	27.4	37.3
No international trade frictions									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	30.9	9.3	31.8	9.1	12.3	6.8	17.4	12.6	37.1
EU brands	55.6	73.2	9.6	73.9	67.3	81.5	59.3	71.7	10.6
JPN brands	8.1	13.0	48.5	13.0	14.7	9.5	18.6	12.6	43.8
Other brands	5.4	4.5	10.1	4.1	5.7	2.2	4.7	3.2	8.6
Home brands				51.3	6.7	52.4	14.8	28.6	37.1
No multinational production frictions									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	30.9	9.9	33.0	9.3	12.0	7.1	16.9	12.5	38.2
EU brands	56.5	74.3	8.7	75.6	69.5	81.7	61.7	72.6	9.9
JPN brands	8.9	11.5	49.2	11.2	13.2	9.1	16.9	11.8	44.3
Other brands	3.7	4.3	9.1	3.9	5.3	2.1	4.4	3.1	7.6
Home brands				53.9	8.7	52.0	18.9	29.1	38.2
No tariffs, trade or multinational production frictions									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	25.7	10.7	27.1	10.4	13.8	7.4	20.0	14.7	33.9
EU brands	44.8	71.8	12.0	72.2	65.5	81.1	55.8	68.8	12.7
JPN brands	7.7	12.8	49.0	13.2	14.8	9.2	19.2	13.0	43.6
Other brands	21.8	4.7	12.0	4.2	6.0	2.3	5.0	3.5	9.7
Home brands				50.3	3.7	53.8	10.4	25.6	33.9

Table B.4: Taste heterogeneity counterfactuals: Average area-level market shares of brand nationality across markets (%)

All countries have French tastes for characteristics									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	35.7	5.6	16.5	8.8	6.5	6.6	12.2	11.8	13.5
EU brands	57.6	73.8	6.8	71.5	68.1	82.6	56.7	69.4	1.9
JPN brands	4.6	17.2	62.7	13.8	21.7	8.8	20.6	13.9	69.3
Other brands	2.1	3.4	14.0	5.8	3.8	2.0	10.5	4.9	15.2
Home brands				42.3	8.1	52.3	11.8	31.2	13.5
All countries have US tastes for characteristics									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	24.3	3.6	34.5	4.3	6.5	2.8	9.1	8.0	39.6
EU brands	59.4	85.0	30.0	87.4	67.8	86.5	73.7	75.4	9.5
JPN brands	13.8	9.4	34.4	7.5	20.7	9.2	15.6	13.6	42.9
Other brands	2.5	2.1	1.0	0.8	5.0	1.5	1.6	3.0	7.9
Home brands				80.4	0.3	11.4	21.6	28.1	39.6
All countries have German gas prices									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	32.0	8.9	34.9	8.3	10.1	6.6	16.0	11.5	35.1
EU brands	55.3	75.8	8.7	77.0	69.1	82.6	62.9	74.2	8.5
JPN brands	8.5	11.3	47.7	10.9	16.2	8.8	16.9	11.4	46.0
Other brands	4.2	4.0	8.7	3.7	4.6	2.0	4.3	2.9	10.3
Home brands				55.4	9.0	52.2	18.2	30.4	35.1

Table B.5: Home preference counterfactuals: Average area-level market share of brands across markets (in percentage)

No home preference, homogeneous, with brand-market controls									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	31.2	8.9	34.1	10.9	11.7	8.5	17.4	13.2	26.1
EU brands	56.4	75.7	8.5	70.2	69.3	76.9	59.3	70.2	12.1
JPN brands	8.3	11.3	48.3	14.3	13.6	11.9	18.7	13.2	52.2
Other brands	4.1	4.0	9.1	4.6	5.3	2.7	4.7	3.4	9.5
Home brands				41.5	4.8	37.8	10.4	20.8	26.1
No home preference, country-specific, with brand-market controls									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	31.2	8.9	34.1	9.1	12.0	9.9	17.7	13.9	36.2
EU brands	56.4	75.7	8.5	75.1	68.7	72.9	58.4	68.6	10.2
JPN brands	8.3	11.3	48.3	11.9	13.8	14.1	19.1	14.0	45.3
Other brands	4.1	4.0	9.1	4.0	5.5	3.1	4.7	3.6	8.3
Home brands				51.4	2.8	27.9	8.6	16.9	36.2
No home preference, homogeneous, no brand-market controls									
	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	31.2	8.9	34.1	12.2	11.9	9.5	18.0	14.0	20.1
EU brands	56.4	75.7	8.5	66.7	68.9	74.1	57.9	68.4	13.3
JPN brands	8.3	11.3	48.3	16.0	13.8	13.5	19.3	14.0	56.3
Other brands	4.1	4.0	9.1	5.1	5.4	3.0	4.8	3.6	10.3
Home brands				34.4	3.4	30.6	7.6	16.4	20.1

Table B.6: Taste counterfactuals: Change in market share (in percentage points)

Change to French Tastes	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	4.5	-3.3	-17.6	0.5	-4.8		-3.8	0.2	-26.1
FRA brands	1.0	-4.5		3.1	-4.2		3.9	0.3	
DEU brands	-3.5	1.5	-1.4	-13.1	5.7		-3.0	-6.0	-6.2
JPN brands	-3.7	5.8	14.4	2.9	8.6		3.7	2.4	26.4
Other brands	1.8	0.4	4.5	6.6	-5.3		-0.8	3.1	5.9
Home brands				-13.1	-0.9		-6.3	0.9	-26.1
High-efficiency models[a]	3.5	31.1	36.8	11.5	23.2		21.8	10.7	46.3
Change to US Tastes	BRA	BEL	CAN	DEU	ESP	FRA	GBR	ITA	USA
US brands	-6.9	-5.3	0.5	-4.1	-4.7	-3.8	-6.8	-3.6	
FRA brands	-5.9	-14.4		-7.0	-22.8	-40.9	-8.1	-3.5	
DEU brands	1.6	25.0	16.0	25.0	27.2	40.0	16.9	6.2	
JPN brands	5.5	-2.0	-13.8	-3.4	7.7	0.4	-1.3	2.1	
Other brands	5.6	-3.3	-2.6	-10.4	-7.3	4.3	-0.7	-1.3	
Home brands				25.0	-8.8	-40.9	3.4	-2.2	
High-efficiency models[a]	-35.4	-35.2	-38.5	-44.8	-47.3	-47.5	-33.5	-23.8	

[a] High-efficiency models are those above the share-weighted median fuel efficiency for that country.